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Examining Students' Metacognitive Awareness Through Analysis of Student-generated Learning Responses

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Work-in-Progress: Examining students' metacognitive awareness through analysis of student-generated learning responses

Abstract

This work-in-progress provides a preliminary exploration of students' metacognitive monitoring abilities by analyzing written self-evaluations of statics problems. Metacognitive approaches to learning encourage students to examine their own thinking processes as a means of deepening their understanding. We used qualitative coding to analyze students' level of metacognitive awareness regarding both their ability to solve a given problem and their ability to identify sources of error. The full data set includes 10 response sequences (homework solution and student writing about their solution) from 69 students. In this paper, we present the analysis of two of these sequences, one from early and one from later in the semester. The findings show that for both assignments, about half the students recognized their inability to solve the problems correctly, though in both cases the groups were split between those who could accurately identify one or more sources of error and those who could not. This finding points to the need for teaching practices that can help students develop the ability both to accurately assess their performance and, perhaps more importantly, identify sources of error and confusion that can then lead to successful learning.

Introduction

Metacognition is critical for student learning and is particularly salient in engineering education because of its close links to problem-solving[e.g., 1, 2-4]. While significant work on metacognition has been done in other learning domains, few researchers have focused on engineering or provided strategies that engineering educators can use to help students develop metacognitive skills focused on problem-solving practices central to engineering work. To help address this gap, we draw on work in both writing-to-learn and reflective practice to explore students' current levels of metacognitive awareness, and to identify fruitful interventions for further investigation.

Metacognition

Broadly, metacognition is the ability to understand and be aware of one's own thinking processes. Metacognitive approaches to learning encourage students to examine their own thinking processes as a means of deepening their understanding[2, 5, 6]. Cunningham et al.[1] highlight the two broad categories of metacognition explored in the literature: *knowledge* of cognition (including understanding people, tasks, and strategies) and *regulation* of cognition (including planning, monitoring, controlling, and evaluating one's own practices in learning and doing). In our study, we focus on students' knowledge of engineering tasks and their corresponding ability to effectively monitor their task performance. To do so, we look at writing-to-learn (WTL) and reflective practice strategies as tools to both support and evaluate students' monitoring capabilities.

Writing-to-Learn

The Writing-to-Learn (WTL) movement began in the 1980s in the wake of Emig's seminal 1977 article, "Writing as a Mode of Learning," in which she described ways in which the act of writing both corresponded to and supported the cognitive processes of learning [7]. In the decades since, writing-to-learn has become ubiquitous in many fields across all levels of education. Hundreds of articles have been written both theorizing and empirically testing writing as a tool for learning, and studies have demonstrated that writing can support learning in mathematics, the sciences, the social sciences, and the humanities[e.g., 8-15]. Meta-reviews, though limited, generally find support for WTL practices. For example, Bangert-Drowns, Hurley, and Wilkinson's 2004 meta-analysis of studies on the impact of writing-to-learn on learning[16] indicates that WTL prompts that are frequent and calibrated to the students' learning context "produced small, positive effects on school achievement" (p. 49). Most relevant to our work, they found that short, frequent prompts that required students to "reflect on their current knowledge, confusions, and learning processes" were the most effective writing-to-learn exercises, yielding better outcomes than writing assignments that did not focus on these metacognitive practices (p.50).

Reflective Practices

To look more closely at metacognition in engineering students, we focus on students' ability to both identify current knowledge gaps and ask questions that can address those gaps to support learning. Asking students to generate their own questions is a form of metacognition that provides a clear window into sources of student confusion [e.g., 17, 18].

Many researchers have investigated the steps needed to generate effective question-asking in students [e.g., 19-21]. Historically, studies involving self-generated questions in the STEM fields have focused on improving reading comprehension, formulating research questions, and learning new content through group discussions[20], with limited exploration of improving students' ability to articulate questions to support problem-solving activities. King[17] used question prompts such as "What is our plan?," "What do we know about the problem so far?," and "Do we need a different strategy?" to guide elementary school students through the various stages of problem-solving. These prompts led guided questioners to outperform their unguided peers and controls on a written test of problem-solving as well as on a new task. These students also asked more strategic questions during the problem-solving process. King postulated that the question prompt taught students how to be more effective problem-solvers.

One of the first steps in framing a useful question, however, is recognizing knowledge deficits[21]. To that end, it is not surprising that good students realize that they do not understand a concept more often than poor students[19]. At the same time, research by Kruger and Dunning suggests that the less domain knowledge or competence individuals possess in an area, the less able they are to assess their own performance and the more likely they are to overrate their ability; they term this phenomenon "unskilled and unaware."[22] Thus students who most need help may be least able to identify their need and ask effective questions that support self-regulation.

Given this potential deficit, we are interested in strategies that encourage both accurate self-monitoring and effective question-asking. Our long-term goal is to develop a heuristic that trains students to ask more questions that effectively support their learning and problem-solving. To develop such a heuristic, we must first identify the source of college-level engineering students' difficulty in formulating questions: Are students able to recognize when they are confused? Are they able to accurately identify what confuses them? Such questions are directly linked to students' metacognitive awareness, and specifically to their ability to monitor their learning.

One way to explore students' metacognitive awareness is to have them rate their confidence regarding homework problems they complete. As noted above, there is evidence that those who are poor at assessing their own skill levels are likely to be over-confident [e.g., 22, 23]. To explore this possibility in engineering students, we can both compare students' level of confidence to their performance and assess whether their self-described areas of confusion match the kinds of errors they make. By tracking such comparisons across a semester, we can see whether there is change over time as students gain domain knowledge in a course. Examining students' self-reported confusion also allows us to assess their understanding with regard to procedural or conceptual issues in statics. We can distinguish whether students' questions focus on deeper conceptual issues or on more surface procedural tasks. This distinction is relevant, as recent work suggests that conceptual questions are most helpful for improving understanding[24].

In this work-in-progress, we provide initial findings with respect to students' capacity for accurate monitoring in statics. Data are drawn from an ongoing study in which students were asked to reflect and write about their problem-solving ability in an engineering statics course[3]. Specifically, they were asked to identify the source(s) of their confusion with reference to select homework problems. The students wrote in two distinct phases. They first described their confusion about a homework problem before instructor input. After the question was reviewed in class, students wrote again, this time reflecting on the source of their initial confusion.

Although the study originally focused on achieving measurable improvements in conceptual understanding, initial findings showed limited effects on students' performance based on an analysis of course grades. At the same time, interview and survey data indicated that many students found the writing intervention helpful[3], which prompted new research questions regarding the links between the in-class writing prompts and students' metacognitive awareness of their statics knowledge. To better understand these links, we examine students' homework and in-class responses to answer the following research questions:

- RQ1. To what extent were students able to accurately assess their performance and their understanding?
- RQ2. Did students' ability to assess their performance and their understanding change over time?

In this paper, we report findings from our initial exploration of the data.

Method

To address our research questions, we employed qualitative coding to first analyze the errors on students' homework and their in-class self-assessments and then compared their performance to their assessment.

Data Source

As reported in Goldberg et al.[3], data were collected from three sections of an introductory statics course; one section was taught in the spring and two were taught the following fall, all by the same instructor. The three sections included a total of 69 students; however, not all students completed all homework assignments, and not all students completing an assignment attended class to provide an in-class survey response.

As with many statics courses, students completed weekly out-of-class problem sets focused on concepts such as expressing forces and moments as vectors, drawing free-body diagrams, and writing and solving equilibrium equations. The course included ten problem sets across the fifteen-week semester. On the day each problem set was due, students were asked in class to rate their confidence in their solution to one selected problem from the set, then write about any confusion they had about the concepts or computations required to solve the problem. They were also asked to write a question to help clarify their confusion. The professor then demonstrated the solution to the class as students corrected their own work. Finally, students revisited their initial response and wrote out their revised understanding of the problem. The instructor read the responses after class, and gave feedback to students on any lingering questions or confusion they expressed. To capture student work for subsequent analysis, both the homework assignment and the in-class writing were collected and scanned before being returned to students.

To explore students' capacity for self-assessment, we focus on the first two questions in the in-class response, shown in Figure 1:

Figure 1: In-class Questions

1. Circle the letter that best describes your understanding of the starred homework problem on this assignment:
   a) I did not understand the problem and didn't really know how to approach it.
   b) I understood some aspects of the problem, but wasn't very confident in how to solve it.
   c) I was not 100% certain, but for the most part I knew what I was doing.
   d) I felt that I had a complete understanding of the problem.

2. If you answered a, b, or c above: In at least 3 sentences, describe what confused you about this problem, or what you were unsure about. When writing, imagine that you are talking to another student in the class.
If you answered d above: In at least 3 sentences, explain to another student how you solved the problem.

The present analysis includes two assignments, one from the beginning of the semester (HW2) and one from the end of the semester (HW9) to provide a preliminary longitudinal perspective:

- HW2 asked students to calculate the 3-dimensional moment acting on the base of a traffic light due to an applied tension force given the geometry of the system.
- HW9 asked students to determine the axial force, shear force and bending moment acting on a specific point along a 2-dimensional beam given the physical constraints on the beam and a distributed load acting along a portion of the beam span.

Future analyses will include all assignments and consider students' questions as well as their revised understandings, but in this exploratory study, these two in-class responses from these two assignments offer provisional answers to our primary research questions.

Data Analysis

Data analysis followed the general procedures for qualitative coding outlined by Miles et al. [25] and proceeded in two phases.

In Phase 1, researchers used descriptive coding[25] to identify the errors made in students' homework and described in students' in-class responses to Question 2. Two researchers (Goldberg and Groen) worked together to generate an initial list of error codes that included all general types of errors that students could make across all classes of assigned statics homework problems. Goldberg applied the codes to students' homework solutions, while Groen and Lutz applied the codes to students' in-class writing. All three authors met regularly to revise the list of codes and the definitions of each code. Appendix A includes the final list of error codes applied to both data sources.

In Phase 2, Groen and Lutz compared each student's homework error codes to his or her in-class writing to generate a holistic code[25] for that student's level of metacognitive awareness. The initial codes for this metacognition were drawn from Kruger and Dunning's concept of "unskilled and unaware"[22], which we extrapolated to include the opposite end of the spectrum: skilled and aware. Effectively, students could theoretically fall into one of four groups based on their *accuracy* in solving the problem and their *awareness* in self-assessment: i.e. students could be right or wrong on the homework itself (skilled or unskilled), and be aware or unaware of their accuracy. As defined in Figure 2, the matrix of awareness and accuracy is described by four groups: Unskilled & Aware, Skilled & Aware, Skilled & Unaware, and Unskilled & Unaware.

Figure 2: Initial metacognitive quadrants

Unskilled & Aware: Students solved the problem incorrectly, and knew that they were incorrect.	**Skilled & Aware:** Students solved the problem correctly and knew they were correct.
Unskilled & Unaware: Students solved the problem incorrectly, but thought they were correct.	**Skilled & Unaware:** Students solved the problem correctly, but thought they were incorrect.

Awareness ↑

Accuracy →

In practice, however, additional categories emerged based on nuances in the relationships between students' performance and their self-assessments; both Unskilled & Aware and Skilled & Unaware each include three different subcodes, shown in Table 1.

Table 1: Final Codebook

Code	Subcode	Definition	Conditions
Unskilled & Unaware	(None)	The student got the wrong answer on the homework, but thought they had the right answer.	HW: Incorrect Q1: d Q2: Incorrect
Unskilled & Aware	*Lost*	The student knows the homework is wrong, but has no idea why.	HW: Incorrect Q1: a or b Q2: Described difficulty knowing where to begin, asks a question that has no bearing on the problem
	Uninformed	The student knows the homework is wrong, but incorrectly identifies why.	HW: Incorrect Q1: b or c Q2: Describes a problem unrelated to any of the actual sources of error
	Informed	The student knows the homework is wrong and has some general idea why.	HW: Incorrect Q1: b or c Q2: Described one or more of the errors the student made on the HW
Skilled & Unaware	*Lost*	The homework is correct but the student has no idea why.	HW: Correct Q1: b or c Q2: Student did not know the HW was correct
	Unsure	The homework is correct, but the student lacked confidence in his/her answer.	HW: Correct Q1: c Q2: Student described points of confusion and potential errors in the homework
	Wrong	The homework is correct but the student explained the solution incorrectly.	HW: Correct Q1: d Q2: Explanation was incorrect
Skilled & Aware	(None)	The homework is correct; the student knew it was correct and explained it correctly.	HW: Correct Q1: d Q2: Correct explanation

Using an iterative analysis procedure, each coder analyzed one homework assignment for one class section. The coders then met to compare and discuss initial results. Once coding discrepancies were identified, a final codebook was agreed upon by both coders to finish analysis. As a result, the coders arrived at eight possible metacognitive levels represented in the data based on the homework (HW), the student's response to the first in-class question rating their understanding of the problem (Q1), and their in-class explanation of either their confusion or their problem-solving process (Q2). All in-class responses were re-coded accordingly with coders randomly checking in with one another to ensure the quality of the codebook. As indicated by the conditions listed in Table 1, students' metacognitive level was determined by first rating them as skilled or unskilled based on their homework solution (i.e. right or wrong) and then rating their awareness based on both their level of confidence (Q1) and the accuracy of their explanation (Q2).

Results and Discussion

RQ1: Student Assessment of Performance and Understanding

With respect to metacognitive level, Table 2 summarizes the total number and the percent of students in each category for Homeworks 2 and 9 (HW2 and HW9).

Table 2: Levels of Metacognitive Awareness

Code	**HW2 (58 complete+ responses)**		**HW9 (41 complete+ responses)**	
	N	**%**	**N**	**%**
Unskilled & Unaware	**6**	**10%**	**6**	**15%**
Unskilled & Aware (Total)	**32**	**55%**	**18**	**49%**
Lost	*9*	*16%*	*0*	*0%*
Uninformed	*3*	*5%*	*9*	*22%*
Informed	*20*	*34%*	*11*	*27%*
Skilled & Unaware (Total)	**11**	**19%**	**8**	**19%**
Lost	*0*	*0%*	*1*	*2%*
Unsure	*11*	*19%*	*7*	*17%*
Wrong	*0*	*0%*	*0*	*0%*
Skilled & Aware	**9**	**16%**	**7***	**17%**

+ A complete response included a completed homework problem as well answers to Questions 1 and 2 on the in-class writing. Students who did not complete the homework were excluded even if they completed a survey because the written homework solution could not fully capture sources of error, rendering comparison impossible.

* Includes 3 students who effectively completed the problem correctly but had a minor calculation error that resulted in an incorrect final answer.

As the data indicate, students spanned the full spectrum of categories, with one exception: no students in either homework were in the Skilled & Unaware-Wrong category.

In both homework assignments, the largest group of students (approximately half in both cases) fell into the Unskilled & Aware category. That is, the students recognized their inability to solve the problems correctly, though in both cases the groups were split between those who could accurately identify one or more sources of error (the Informed group) and those who could not (the Lost and Uninformed groups).

Both the prevalence of students with low awareness (Unskilled & Unaware, but also Unskilled & Aware-Lost or -Uninformed) and, at the other end of the spectrum, the substantial percentage of students who were Skilled & Unaware-Unsure (19% and 17% in HW2 and HW9, respectively) points to the need to help students more effectively evaluate their own levels of skill and understanding.

With respect to the absence of students in the Skilled & Unaware-Wrong category, several explanations are possible. This category may occur when students had followed an outside source (e.g. online solutions, another student's work) but had not worked through the problem on their own; in that case, the absence may reflect the lack of such behaviors. Similarly, the category could include students who possess only procedural knowledge; that is, they are able to follow formulas, but lack a clear understanding of the conceptual principles involved in the problem. In that case, the absence of students in this category may indicate that purely procedural knowledge may be insufficient to correctly complete the types of problems assigned. It may be that students in either of these groups simply are not able to provide a meaningful explanation and fall into Skilled & Unaware-Lost instead; analysis of the remainder of the homework assignments should clarify this issue.

To determine whether students' level of awareness showed any correlation with the types of errors they were describing, we mapped error types described in Q2 against levels, as shown in Table 3 (note that the table excludes Skilled & Aware students since they did not make errors and Skilled & Unaware-Wrong since that group was empty).

Table 3: Summary of Error Patterns

	HW2			HW9		
	Vectors	**Math. Operations**	**Statics-Specific Concepts**	**Vectors**	**Math. Operations**	**Statics-Specific Concepts**
Unskilled & Unaware	**12**	**4**	**0**	**2**	**0**	**5**
Unskilled & Aware (Total)	**48**	**22**	**0**	**5**	**3**	**40**
Lost	12	5	0	0	0	0
Uninformed	2	2	0	2	1	15
Informed	34	15	0	3	2	25
Skilled & Unaware (Total)	**12**	**8**	**2**	**3**	**0**	**11**
Lost	0	0	0	1	0	0
Unsure	12	8	2	2	0	11

The data set is too small to allow meaningful statistical analysis, but visual inspection shows no clear pattern of interaction with the types of errors students made. Instead, the errors appeared more closely linked to the problem itself. In HW2, two-thirds of the errors students described involved vectors, with another third involving mathematical operations (cross-products and trigonometry or geometry); in HW9, more than three-fourths of the errors students described were statics-specific concepts.

RQ2: Changes Over Time

With respect to changes over time, Table 2 suggests no major change in the overall metacognitive awareness of the class, with approximately the same percentage of students in each of the four major categories in both homework assignments. Within the Unskilled & Unaware group, however, no students were Unskilled & Aware-Lost at the end of the semester, suggesting that all students who completed the assignment and the survey could at least begin to describe where they perceived their confusion. At the same time, the percentage of students in the Unskilled & Aware-Uninformed category grew; one possibility here is that while more students felt able to describe perceived conceptual errors, their ability to accurately identify those errors did not necessarily increase.

For the 38 students who completed the homework problems and surveys for both HW2 and HW9, comparisons on a student-by-student basis show a similar lack of pattern. Table 4 summarizes the number of students moving from a given category in HW2 to a given category in HW9. For example, for HW2 a total of 7 students were categorized as Unskilled & Aware – Lost (summing across this row). For HW9, 6 of these 7 students were categorized as Unskilled & Aware – Informed, while 1 was categorized as Skilled & Aware.

Table 4: Patterns of Change in Metacognitive Level – Number of Student Moving *From* a Given Category in HW2 *To* a Given Category in HW9

HW9 / *HW2*	Unskilled & Unaware	Unskilled & Aware			Skilled & Unaware		Skilled & Aware
		Lost	Uninformed	Informed	Unsure	Lost	
Unskilled & Unaware					1		
Unskilled & Aware - Lost				6			1
Unskilled & Aware - Uninformed			2			1	
Unskilled & Aware - Informed	2		2	3	4		2
Skilled & Unaware - Unsure	2		3		1		2
Skilled & Unaware - Lost							
Skilled & Aware	1		2	1	1		1

As can be seen in Table 4, similar numbers of students grew more aware (e.g. moving from Unskilled & Aware-Uninformed to Unskilled & Aware-Informed), grew less aware (e.g. moving from Skilled & Aware to Unskilled & Aware-Uninformed), or stayed the same. The small number of students in this data set, moreover, limit our ability to identify any meaningful patterns; i.e. although all students in the lowest metacognitive levels (Unskilled & Unaware, Unskilled & Aware-Lost, or Unskilled & Aware-Uninformed) moved out of those positions, the number of students in this group is too small to indicate any trend, particularly since several other students moved down into those categories.

Given that, as Kruger and Dunning note, awareness seems to coincide with domain knowledge[22], one possible explanation for the lack of clear development is that while students are building domain knowledge in statics broadly over the course of the semester, the specific concepts needed in the two homework assignments are different enough that the broad growth in domain knowledge does not support increased awareness overall. This possibility suggests that even if students did make gains in their ability to self-monitor within a subset of statics concepts, they are not able to transfer those gains to another subset of concepts. Here, too, analysis of the remaining homework sets will provide additional data.

Conclusions and Future Work

Findings from this initial analysis demonstrate that while the available data is usable as a means to identify students' metacognitive awareness levels, this data set shows a high degree of variation both within and across assignments. At the same time, the high percentages of students with low monitoring skills (Unskilled & Unaware, Unskilled & Aware-Lost, Unskilled & Aware-Uninformed, and potentially the Skilled & Unaware-Unsure groups) points to the need for teaching practices that can help students develop the ability to both accurately assess their performance and, perhaps more importantly, identify sources of error and confusion that can then lead to successful learning.

In looking toward such practices, the in-class approach used in this project shows notable potential. While this initial analysis showed no change over time, we note that the in-class writing was introduced without any form of scaffolding to help students understand metacognition broadly or learn to identify errors and ask useful questions. Scaffolding has been shown to help students generate questions in the context of improving students' reading and listening comprehension[26], as well as improve question-asking in a problem-solving context[17]. We thus anticipate that the complete analysis of the data, including not only all of the assignment sets, but also the remaining in-class items (questions posed and revised understandings) will help identify fruitful approaches to such scaffolding. Similarly, analyzing students' written responses with respect to conceptual versus procedural knowledge[27] can further illuminate the kinds of scaffolding needed. Venters et al.[27, 28] and Moore[29], for example, both suggest that conceptual and procedural knowledge are both critical in statics; Venters' work also suggests that writing prompts can play a role in supporting conceptual knowledge in this domain.

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Appendix A: Error Codes

The errors students made on their homework and described in their responses were divided into three broad categories: vectors, mathematical operations, and statics-specific concepts. Across the homework and responses, errors in this categories were as follows:

Vectors

- Position vector
- Unit Vector
- Force vector
- Moment vector
- Vector components

Mathematical Operations

- Cross product
- Solving systems
- General math
- Trig & Geometry

Statics-Specific Concepts

- Free body diagrams
- Force-Moment relationships
- Cutting
- Load location
- Distributed load
- 2-Force member
- Shear & bending moment diagrams
- Solving problem as a couple

Note that for Question 2 on the in-class writing, these error codes identify only the topic of the error; they do not capture whether the student described the error in procedural or conceptual terms. On the homework, of course, they represent procedural errors since the homework represents only the student's process, not his/her thinking.